# Material characterization

While designing and providing robust production processes for demanding sheet metal components, manufacturing companies are under constant time, cost and quality pressure. To meet the economic and qualitative challenges arising in this context, the FEM (Finite Element Method) simulation is employed today for designing such robust production processes. Here, the prediction quality of the calculated simulation results is particularly dependent on modeling the materials used as precisely as possible. Thus, the plastic flow of sheet metal materials in the forming simulation is predicted by high accuracy yield locus models like Barlat YId2000-2d or Banabic BBC05. However, to ensure realistic simulation results and high simulation accuracy using these models, the parameters of the yield locus definitions usually must be determined and validated via a large number of tests. The determination and validation of the material parameters ("material characterization") for the selected material model thus represents an essential factor in the development and design of successful and robust forming processes.

### **Inverse Parameter Identification**





- the use of a FE software,
- the programming of an inverse approach,

but is capable of calculating the material parameters directly from the experimental measurements.

# ANNdirect

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A new machine learning based method to determine directly validated material model parameters for sheet metal forming simulations

## **FE Simulations on HAWK**

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Around 5 million of FE simulations were performed automated and distributed parallel on many compute nodes of the system HAWK. MPI driven parallelization distributed the computation on many compute nodes. The use of the RAM-Disk concept accelerated the computation performance and made the access to hard storage redundant during the computations. Upon completion of the executions, the extracted data were exported at once to workspace leaving the computational resources free as soon as computations on a node was finished. By this distribution concept as many nodes as possible can be used, without causing any performance degradation on any node. Within a node, all the CPUs are loaded and only RAM is used also for the complete storage during the execution of the job. In these aspects, all the CPU resources on each node (without hyper-threading) were used 99-100% during all instances of computations.



### **ANN-Training**

The ANN-Training part was conducted under the supervision of Mr. Hoppe (HLRS) and as a collaborative work with his team. The ANN-training code is tested on many CLX-AI nodes (each with: 8 GPUs, Nvidia Tesla V100 32GB Memory). Both parallelization within a node and distribution on many nodes were programmed. Performance tests using the whole dataset for parallelization were conducted on many nodes. Since the test problem was a multi-regression problem 1D convolutional neural networks were programmed. The programming environment was TensorFlow-2 and basically KERAS library was used. The best validation loss value of 0.004 for predicting material parameters simultaneously was acchieved.



Ite		
		Ideal extrapolation regarding 16 cores
		Ideal extrapolation regarding 128 cores
		—Measured number of Simulations in 60 seconds
0	1200	

		Recorded
		Ideal (Linear extrapolation based on configuration up to 2 nodes)
0	35	

